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Aggregate accounting research and development expenditures and the prediction of real gross domestic product

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ABSTRACT

The role of accounting information for public policy making has received increased attention in recent years. Konchitchki and Patatoukas (2014a,b) demonstrate that growth in aggregate accounting earnings can predict future growth in *nominal* and *real* Gross Domestic Product (GDP). We extend the micro to macro literature by decomposing earnings into the R&D and pre-R&D components. Using the Almon (1965) finite distributed lag model, we find that both components can predict future *real* GDP growth with different lead-lag structures. Importantly, this decomposition significantly increases the explanatory power of the predictive model using accounting information. Aggregate accounting R&D can predict real GDP through the personal consumption, business investment, and net export channels of GDP. Our study extends prior research on the forecasting usefulness of accounting information at the aggregate level and has practical implications for macro forecasting and for public policy making regarding innovative activities of publicly listed firms.

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1. Introduction

The role of accounting information for public policy making has received increased attention in recent years. Important policy decisions at the Federal Reserve about money supply and interest rates depend, in part, on predictions about future GDP growth. Konchitchki and Patatoukas (2014a) (KP) find that aggregate accounting earnings growth is a leading indicator of future *nominal* Gross Domestic Product (GDP) growth up to three quarters ahead. KP (2014b) decompose aggregate earnings into asset turnover and profit margin and show that this decomposition significantly increases the predictive ability with respect to future *real* GDP growth. The KP studies are among the first to show the usefulness of accounting data in predicting GDP, an important measure for public policy making.[1]

We extend KP (2014a, b) by decomposing total earnings into its research and development (R&D) and pre-R&D earnings components. A major reason for decomposing earnings into R&D expenditures and pre-R&D earnings is that it allows these two earnings components to exhibit different lag structures with respect to aggregate output, which significantly increases the explanatory power of aggregate accounting data with respect to future real GDP growth. Thus, our model, which explicitly incorporates multiple lagged values of aggregate R&D expenditures, provides meaningful incremental insights on the predictive ability of aggregate accounting data otherwise unaccounted for in the KP (2014a, b) models.

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[1] GDP is the most comprehensive and closely watched measure of national economic output and is the most important variable in analyses of economic growth (Pritzker, Arnold, and Moyer 2015).

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We study aggregate R&D expenditures because prior theory studies assert that R&D expenditures constitute the main input of the innovative processes of the economy (e.g., Solow, 1957; Griliches, 1979; Griliches and Mairesse, 1981; Grossman and Helpman, 1990). Empirical research generally supports the claim that technological innovations play an important role in economic performance at the firm, industry, and national levels (e.g., Comin et al., 2006; Hall, 2011; Klenow and Rodríguez-Clare, 1997; Mairesse and Mohnen, 2004). These innovations can take the form of process or product innovations, the latter of which entail products new to the firm (but not to the market), and products new to the market. Such innovations help firms successfully compete against rivals by allowing them to conduct business either at a lower cost or in a way that leads to product differentiation and a premium price (Griffith et al., 2006; Porter and Millar, 1985). Technological innovations can improve productive output via three primary channels.

First, given the same product quality, better technology leads to better productivity (*process innovation*), i.e. more output per unit of input, which means firms can produce products or services at lower costs (Friedlaender et al., 1983; Griliches and Mairesse, 1981; Hall, 2011; Lengnick-Hall, 1992). If firms pass these cost savings on to their customers, lower production costs mean they can gain competitive advantages over their rivals in the product markets, which translates to higher sales and profits for these firms.

Second, better technology can lead to better-quality products or services (*product innovation*) (Hall, 2011; Porter and Millar, 1985; Thatcher and Oliver, 2001), which allows firms to demand premium prices that add value to the economy (Laurion and Patatoukas, 2016). A classic example of the second channel is the Apple's iPhone, a revolutionary handheld electronic device that created an entire smartphone industry (Vogelstein, 2008). Being the first mover, Apple reaped enormous profits from the iPhone. This technology development can spill over to other products and to other firms that can contribute to the aggregate output of the economy.

Third, better technology can improve the flow of information and cooperation among different firms in the supply chain (another form of process innovation) (Belderbos et al., 2004; Porter and Millar, 1985). For example, by implementing technology improvements that allow more efficient communication, coordination, and transactions among its suppliers and customers, Apple can receive better and timelier input from their suppliers and, in turn, provide better and timelier output to customers, thus enhancing the productivity of both its suppliers and customers. This translates into more value creation for all parties in the supply chain.

We expect the lead-lag relation between R&D expenditures and future GDP growth to be much different from the lead-lag relation between other earnings components and future GDP growth because it takes much longer for R&D than for other earnings components to yield commercially viable products that contribute to GDP. We find that both components of aggregate earnings can predict future real GDP growth, with the R&D component having a much longer lag structure than the pre-R&D component. We also show that accounting for this longer lag structure for R&D expenditures significantly enhances the predictive power of the model. We use the Almon (1965) distributed lag model to demonstrate this improved predictive ability, which is appropriate in this setting and is a unique contribution to this literature stream.

Our study is related to the literature examining accounting information at the aggregate level. (KP, 2014a; KP, 2014b) show that aggregate earnings growth and its profit-related components can predict both nominal and real GDP growth. Others find that aggregate earnings can predict future inflation (Cready and Gurun, 2010; Patatoukas, 2014; Shivakumar, 2007; Shivakumar and Urcan, 2017) as well as restatements in macro forecasts (Nallareddy and Ogneva, 2017). Recently, Abdalla et al. (2021) show that incorporating the continuous flow of accounting data using a dynamic factor model adds incremental value to nowcasting and forecasting GDP and Gross Domestic Income (GDI). Other studies in this literature examine whether the firm-level accounting properties remain relevant at the aggregate level. Such properties include the earnings-return relationship (Ball et al., 2009; Kothari et al., 2006; Sadka and Sadka, 2009), conditional conservatism (Crawley, 2015; Laurion and Patatoukas, 2016), earnings surprises (Gallo et al., 2016), transitory accounting items (Abdalla and Carabias, 2021), and negative earnings (Gaertner et al., 2020). Our study contributes to this literature by being the first to examine the predictability of accounting-based R&D at the macro level.

Our study is also related to the vast literature examining the benefits of R&D activities at all levels of the economy (Ben-Zion, 1984; Chudnovsky et al., 2006; Comin et al., 2006; Griliches, 1979; Griliches and Mairesse, 1981; Hall and Jones, 1999; Hirschey, 1982; Hirshleifer et al., 2013; Hsu, 2009; Jose et al., 1986; Klenow and Rodríguez-Clare, 1997; Lev and Sougiannis, 1996; Mairesse and Mohnen, 2004; Pakes, 1985; Sougiannis, 1994).[2] While this literature is mature, it is surprising that none has examined the predictive content of aggregate R&D expenditures at multiple lags with respect to real GDP growth, with the R&D numbers extracted from firms' accounting statements. Our study seeks to fill this gap.

2. Hypothesis development, research design, and empirical results

2.1. R&D expenditures, pre-R&D earnings, and future real GDP growth

KP (2014b) find that aggregate operating income growth can predict one-quarter-ahead real GDP growth. Because operating income is a core component of earnings, we expect, based on the lag structure documented in (KP, 2014b), that aggregate pre-R&D earnings growth can predict real GDP growth in the short term. However, given prior theories on R&D, we

[2] The research in R&D is vast. Providing a comprehensive review of this literature is outside the scope of our paper.

expect the R&D component of earnings to predict real GDP growth over longer horizons because the effects of R&D investments are distributed across multiple periods and the successive impacts of these R&D investments are collinear. Due to the delayed input–output nature of R&D spending, we use the Almon (1965) distributed lag model to assess how long, on average, it takes a change in aggregate R&D expenditures to impact real GDP growth and how long it lasts once in effect. We do not expect the R&D component to have much short-term impact on GDP because R&D investments take time to materialize into commercial outputs.

We choose the quarterly setting for three reasons. First, aggregate accounting data are potentially important for macroeconomists who most often make quarterly GDP forecasts (Stark, 2010; KP, 2014a; KP, 2014b). Second, using quarterly data gives us sufficient time series observations to better analyze the lead-lag structure of R&D expenditures and future GDP growth, consistent with prior micro-to-macro studies that use Compustat as the main source of accounting data (KP, 2014a; KP, 2014b); Nallareddy and Ogneva, 2017; Patatoukas, 2014; Shivakumar and Urcan, 2017).[3] Third, using quarterly data makes our findings more comparable to those reported in (KP, 2014a; KP, 2014b) who also use quarterly data. To test our predictions, we regress current GDP growth on lagged aggregate accounting R&D growth as follows.

$$G\_GDP_q = \beta_0 + \sum_{t=0}^{k}\beta_{1,\,q\text{-}t}\,G\_XRD_{q\text{-}t} + \sum_{t=0}^{m}\beta_{2,\,q\text{-}t}\,G\_PreRD\_Earn_{q\text{-}t} + \beta_3\,G\_GDP_{q\text{-}1} + \beta_4\,Yield_{q\text{-}1} + \beta_5\,Spread_{q\text{-}1} + \beta_6\,Return\_12_{q\text{-}1} + \varepsilon_q \quad (1)$$

We construct a measure of aggregate accounting R&D growth, G_XRD_q, following the aggregation method used by (KP, 2014a; KP, 2014b). For every firm-quarter, we compute the seasonally adjusted change in quarterly R&D expenditures scaled by one-period lagged quarterly sales and then compute the weighted-average of this change across all publicly traded firms in the same quarter, with the weight being the firms' market capitalization at the beginning of the quarter. We compute the pre-R&D component of earnings by adding back after-tax R&D expenditures to earnings, using the statutory tax rate of 35 percent.[4] We then compute the pre-R&D component of earnings at the aggregate level, $G\_PreRD\_Earn_q$, using the same aggregation method.

G_GDP_q is the annualized seasonally adjusted quarter-over-quarter GDP growth in quarter q.[5] We choose this measure of GDP growth because it is the official measure of GDP growth produced by the BEA and because it conforms to the common practice within the macro-forecasting community that predicts the annualized GDP growth rate.[6] As we want to test the impact of accounting R&D on real production and to account for the long lag of R&D (seven years, as explained later), we adjust all accounting and GDP data for inflation using the GDP deflator.[7] To ensure that accounting R&D is not merely capturing other macro information, we control for lagged values of *G_GDP, Yield, Spread,* and *Return_12* (KP, 2014a; KP, 2014b).[8]

To account for the uncertain nature and lagged effect of innovative activities, we use the Almon (1965) finite distributed lag model to estimate the relationship between R&D and GDP. This is a dynamic model that uses advanced regression analysis techniques for time series data where the effects of the explanatory variables on the outcome variables are distributed across multiple periods and the successive impacts of these treatments are collinear. Because the effect of R&D expenditures on GDP likely fits these criteria, using the Almon model can yield less biased and more consistent estimates relative to the ordinary least square (OLS) method. Additionally, the Almon model allows for the computation of lag length and average duration of the economic benefits of R&D investments.

The Almon method provides another distinct advantage over the OLS method. It transforms the long series of lagged variables into a quadratic function of polynomial degree n, which requires n + 1 regressors rather than a large number of regressors when estimating relationship via OLS.[9] This feature makes the Almon method ideal for time series analysis especially when the data cover a limited time period and the research design requires a long series of lags.[10] For aggregate accounting

[3] Using aggregate indices means we have one observation for each time period, which yields only 45 annual observations for the 1972 – 2016 window. 1972 is the earliest year for which we can obtain annual R&D data because the Securities and Exchange Commissions (SEC) did not mandate the disclosure of R&D spending by public firms before 1972. 2016 is the most recent year for which we can obtain data on all necessary variables as of the time of our analyses.

[4] Applying point-in-time tax rate instead of the fixed 35 percent rate does not qualitatively change the results. It is unlikely that tax plays any role in our R&D-GDP setting because it is the actual R&D expenditures, rather than the tax component associated with those expenditures, that produce new technological innovations benefiting the economy. We simply include the tax component here so that the decomposition can be mathematically correct.

[5] The BEA computes G_GDP as $[(GDP_q/GDP_{q-1})^4 - 1]$, with GDP_q being seasonally adjusted quarterly GDP.

[6] As a robustness check, we run the models using year-over-year percentage growth in quarterly GDP instead of annualized quarter-over-quarter GDP growth and find robust results.

[7] In untabulated analyses, we find that nominal accounting data can also predict real GDP growth. This is because the aggregation process requires the use of accounting ratios, with both the numerators and denominators being scaled by GDP deflators of consecutive quarters. Because these GDP deflators differ by a small amount, the indices of real and nominal aggregate accounting data are quite similar. Nevertheless, we present the results for real accounting data to mitigate any concern that inflation may play a role in our predictive results.

[8] Appendix A summarizes all variables used in this study.

[9] For example, estimating the relationship between GDP and 28 lags of aggregate R&D requires 29 regressors for R&D (including the concurrent value of R&D). The OLS approach will estimate all 29 regressors of R&D, but the Almon approach will only estimate three regressors of R&D (assuming a polynomial degree of two). Adding five lagged values of pre-R&D earnings and four lagged values of other controls means the model needs to estimate 38 regressors using 154 data points. The OLS approach cannot reliably estimate such a model, but the Almon approach can.

[10] This is also the reason why we choose the Almon approach over the vector autoregression (VAR) approach. While the VAR approach can also account for serial correlation, the number of coefficients it needs to estimate grows exponentially with the number of regressors, which prevents it from having long lag series especially given limited time-series data (Robertson and Tallman, 1999; Rouxelin et al., 2018).

R&D growth, we choose lag length of 28 (quarters) and polynomial degree of two. For aggregate pre-R&D earnings growth, we choose lag length of four (quarters) and polynomial degree of one.[11]

The sum of coefficient estimates $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$ on lagged $G\_XRD_{q\text{-}t}$ is of interest because it shows the long-run *cumulative effect* of multiple lagged R&D expenditures on current GDP growth. We expect $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$ to be positive because prior studies document a positive relationship between R&D expenditures and a variety of economic outputs. The mean lag, measured as $\sum_{t=0}^{k}t\beta_{1,q\text{-}t}$ / $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$, is the weighted average lag with the weight being the impact each lagged value of growth in aggregate R&D expenditure has on the current-period growth in real GDP. Thus, the mean lag shows the average number of periods before aggregate R&D investments affect GDP growth. The duration of the impact of R&D investment on future real GDP growth is a function of the cumulative effect of past R&D expenditures, measured as two times the mean lag (Lev and Sougiannis, 1996; Sougiannis, 1994).[12] For aggregate pre-R&D earnings, $\sum_{t=0}^{m}\beta_{2,\ q\text{-}t}$ measures the cumulative effect of past aggregate pre-R&D accounting earnings growth on current GDP growth. We expect $\sum_{t=0}^{m}\beta_{2,\ q\text{-}t}$ to be positive, given the results in (KP, 2014a; KP, 2014b).

Our final sample has 154 quarterly observations from Q1:1978 to Q3:2016. Table 1 provides descriptive statistics for our sample. G_XRD_q has a mean (median) of zero percent (zero percent) and standard variation of 0.20 percent during the sample period (Panel A).[13] While having mean and median of zero, the time series of G_XRD exhibits considerable variation over time with growth rates moving in both positive and negative directions (Fig. 1). Spearman correlations indicate that G_Pre-RD_Earn is significantly associated with contemporaneous G_GDP, consistent with the findings in (KP, 2014a; KP, 2014b) and Shivakumar and Urcan (2017) (Panel B). In contrast, G_XRD is not significantly correlated with concurrent G_GDP due to the delayed effect of innovative activities.

Empirical analyses show that *inflation-adjusted* aggregate earnings can predict future *real* GDP growth up to two quarters ahead with an adjusted R^2 of 12.10 percent (Table 2, column [1]).[14] When R&D and pre-R&D have the same lag structure (lag length of four and polynomial degree of one), aggregate R&D is significant at the 10 percent level at lag two, while pre-R&D earnings is significant at the 1 percent level from lags zero to three (column [2]). While predictability of pre-R&D earnings is comparable to that of aggregate earnings in column [1], the result for aggregate R&D with this short lag structure is very weak, which is logical because it takes several periods for current R&D expenditures to fully affect future GDP output.

When we allow aggregate R&D to have a more appropriate lag structure (lag length of 28 and polynomial degree of two), it becomes strongly predictive of future GDP growth. The R&D series is significant from lags 5 to 24 (column [3]),[15] and has a total effect of 9.63 percent,[16] mean lag of 14.78 quarters (about 3.83 years), and the average duration of 29.55 quarters (about 7.4 years). This means that seasonally adjusted real GDP increases by 9.63 percent in the current quarter if, hypothetically, all publicly traded companies increase their seasonally adjusted real R&D expenditures as a percentage of sales by one percent in each quarter during the five-year period (lags 5 – 24) ending five quarters before the current period. This effect takes on average 3.83 years to materialize and, once in effect, lasts for about 7.4 years. This R&D-GDP relationship is incremental to other known determinants of real GDP growth (column [5]).

[Insert Table 2 here]

Our results are consistent with the previously documented lead-lag relationship between R&D expenditures and the creation of commercially viable technologies. Pakes and Griliches (1980) find that it takes firms 1.6 years to finish an R&D project – from initiating the first R&D expenditures to filing for patent applications. Later, Hall et al. (2001), Hall et al. (2005), and Hirshleifer et al. (2013) document that it takes the U.S. Patent and Trademark Office roughly two years to grant a patent application. The mean lag between R&D expenditures and viable economic output is, thus, approximately 3.60 years. Therefore, our mean lag of 3.83 years between aggregate R&D and GDP (column [4]) appears consistent with prior findings.

The adjusted R^2 is 12.10 percent for aggregate earnings growth (column [1]). It increases to 14.71 percent when we decompose earnings into the R&D and pre-R&D components and restrict their lag structures with respect to GDP to be the same (column [2]). It further increases to 29.82 percent when we allow their lag structures to differ according to their theoretical relationships with GDP (column [3]).[17] Therefore, by decomposing earnings and assigning different lag structures to its components according to R&D theories, we increase the explanatory power of the model by almost 2.5 times from 12.10 percent to 29.82 percent.

[11] The Online Appendix provides more detailed discussion of the Almon lag model and explanations for our choices of the lag lengths and polynomial degrees for our main variables.

[12] Due to the specification of the Almon model, the research design regresses current real GDP growth on multiple lagged values of R&D expenditure growth. The empirical results, therefore, speak to the impact of multiple lagged R&D expenditures on current real GDP. However, the interpretations can extend to the predictive ability of current R&D over future GDP.

[13] The small mean and median values for G_XRDq can be explained by the way R&D expenditures are scaled. G_XRD is the market-weighted average of the firm-level seasonally adjusted changes in quarterly R&D expenditures scaled by one-period-lagged quarterly sales. Because changes in R&D expenditures and changes in one-period-lagged sales are highly correlated (ρ = 0.70), most of the changes in R&D expenditures are offset by changes in sales.

[14] Our results here are based on the Almon distributed lag model. In untabulated analyses using OLS as in KP (2014a, 2014b), we also find that aggregate earnings growth can predict future real GDP growth.

[15] We omit the coefficient estimate for specific lags for brevity. Detailed results are available upon request.

[16] The total effect of 9.63 percent is the sum of the significant parameter estimates on G_XRD.

[17] While pre-R&D earning can predict GDP with a relatively short impact duration, R&D takes much longer to affect GDP (15.78 quarters vs. 0.77 quarter) and has a much longer duration (29.55 quarters vs. 1.55 quarters) (Table 2, column [3]).

Table 1
Descriptive statistics.

Panel A: Summary statistics

Variable description	Variable	Mean	Std. Dev.	Min	p25	Median	p75	Max
Aggregate accounting R&D growth	G_XRD_q	0.000	0.002	−0.008	−0.001	0.000	0.001	0.005
Aggregate pre-R&D earnings growth	$G\_PreRD\_Earn_q$	0.000	0.031	−0.158	−0.009	−0.001	0.011	0.147
Quarterly GDP growth	G_GDP_q	0.027	0.032	−0.082	0.013	0.029	0.042	0.165
Yield (one-year T-bill)	$Yield_{q-1}$	0.052	0.039	0.001	0.016	0.051	0.077	0.161
Spread (Yield on T-bond – Yield)	$Spread_{q-1}$	0.013	0.012	−0.022	0.005	0.015	0.022	0.033
Buy-and-hold return for 12 months	$Return\_12_{q-1}$	0.126	0.177	−0.386	0.021	0.150	0.241	0.669

Panel B: Spearman pairwise correlation, two-sided p-values reported in parentheses

	G_XRD_q	$G\_PreRD\_Earn_q$	G_GDP_q	$Yield_{q-1}$	$Spread_{q-1}$	$Return\_12_{q-1}$
G_XRD_q	1.000	−0.110	0.062	0.202	−0.085	0.082
		(0.17)	*(0.44)*	*(0.01)***	*(0.29)*	*(0.31)*
$G\_PreRD\_Earn_q$		1.000	0.328	−0.112	0.130	0.199
			*(0.00)****	*(0.17)*	*(0.11)*	*(0.02)***
G_GDP_q			1.000	0.150	0.027	0.304
				*(0.06)**	*(0.74)*	*(0.00)****
$Yield_{q-1}$				1.000	−0.600	0.146
					*(0.00)****	*(0.07)**
$Spread_{q-1}$					1.000	−0.104
						(0.20)
$Return\_12_{q-1}$						1.000

Panel A provides summary statistics of the key variables in our final sample of 154 quarters from Q1:1987 to Q3:2016. Panel B provides the correlation matrix of these variables. Appendix A provides detailed descriptions of all variables. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively, using two-tailed tests.

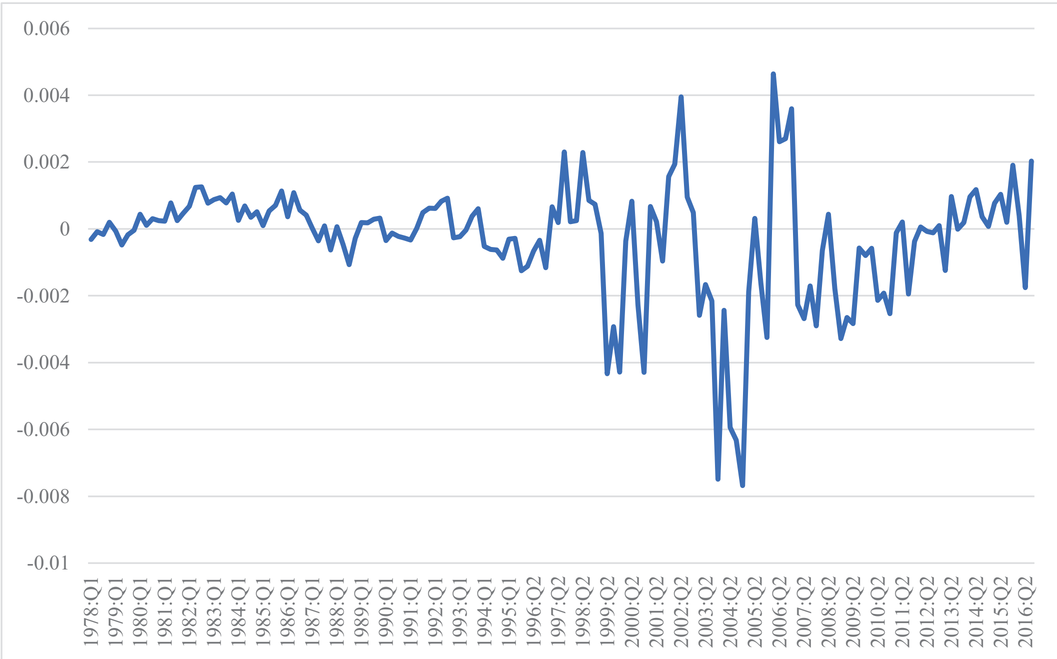

Fig. 1. Aggregate accounting R&D expenditure growth in real terms. This figure presents the time series of aggregate accounting real R&D growth (*G_XRD*). G_XRD is the weighted average of the firm-level year-over-year change in quarterly R&D scaled by one-quarter lagged quarterly sales, with the weight being the firms' market cap at the beginning of the quarter. Quarterly R&D is backfilled by multiplying quarterly sales with the annual R&D to sales ratio.

To further address the concerns that we preferentially give the R&D component a much longer lag than the pre-R&D earnings component, we constrain both components to have the same long lag structure (length of 28 and polynomial degree of two) (column [4]). The 24 additional lags of pre-R&D earnings not only reduce its coefficient estimate from 0.130 (column [3]) to 0.076 (column [4]), but also introduces misspecification in the model, which reduces the adjusted R^2. Therefore, the model with 24 additional lags of pre-R&D components has little incremental explanatory power relative to the model with

Table 2
Aggregate accounting real R&D growth and real GDP growth.

	[1]			[2]			[3]			[4]		
Dependent variable	G_GDP_q			G_GDP_q			G_GDP_q			G_GDP_q		
	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags
$G\_Earn_q \rightarrow_{q\text{-}m}$	0.135	*(4.04)****	0 – 2									
$\mathbf{G\_XRD_q \rightarrow_{q\text{-}k}}$				**0.680**	***(1.86)****	**2**	**0.480**	***(2.70)******	**5 – 24**	**0.556**	***(2.51)*****	**2 – 27**
$G\_PreRD\_Earn_q \rightarrow_{q\text{-}m}$				0.124	(3.68)***	0 – 3	0.130	*(4.82)****	0 – 2	**0.076**	***(3.17)******	**0 – 7**
$G\_GDP_{q\text{-}1}$												
$Yield_{q\text{-}1}$												
$Spread_{q\text{-}1}$												
$Return\_12_{q\text{-}1}$												
For R&D(columns [2]- [6])												
Lag length		N/A			**4**			**28**			**28**	
Polynomial degree		N/A			**1**			**2**			**2**	
Total effect (%)		N/A			0.68			9.63			10.56	
Mean lag (quarters)		N/A			2.00			14.78			9.99	
Mean lag (years)		N/A			0.50			3.69			2.50	
Duration (quarters)		N/A			4.00			29.55			19.98	
Duration (years)		N/A			1.00			7.39			5.00	
For bottom-line earnings (column [1])For pre-R&D earnings(columns [2] – [6])												
Lag length		**4**			**4**			**4**			**28**	
Polynomial degree		**1**			**1**			**1**			**2**	
Total effect (%)		0.41			0.49			0.39			0.61	
Mean lag (quarters)		0.76			1.07			0.77			2.67	
Mean lag (years)		0.19			0.27			0.19			0.67	
Duration (quarters)		1.51			2.15			1.55			5.35	
Duration (years)		0.38			0.54			0.39			1.34	
Adjusted R^2 (%)		12.10			14.71			29.82			29.69	
Sample size		154			154			154			154	

	[5]			[6]		
Dependent variable	G_GDP_q			G_GDP_q		
	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags
$G\_Earn_q \rightarrow_{q\text{-}m}$						
$\mathbf{G\_XRD_q \rightarrow_{q\text{-}k}}$	**0.519**	***(2.15)*****	**6 – 24**	**0.623**	***(2.08)*****	**4 – 20**
$G\_PreRD\_Earn_q \rightarrow_{q\text{-}m}$	0.089	*(2.82)****	0 – 2	0.074	*(2.28)***	0 – 6
$G\_GDP_{q\text{-}1}$	0.022	*(0.23)*		0.013	*(0.13)*	
$Yield_{q\text{-}1}$	−0.092	*(-0.69)*		−0.084	*(-0.58)*	
$Spread_{q\text{-}1}$	−0.192	*(-0.77)*		0.159	*(0.56)*	
$Return\_12_{q\text{-}1}$	0.039	*(3.03)****		0.039	*(2.89)****	
For R&D(column 2 and 3)						
Lag length		28			28	
Polynomial degree		2			2	
Total effect (%)		9.87			10.58	
Mean lag (quarters)		15.34			11.94	
Mean lag (years)		3.83			2.99	
Duration (quarters)		30.67			23.88	
Duration (years)		7.67			5.97	

Table 2 (*continued*)

	[5]	[6]
For bottom-line earnings (column 1)For pre-R&D earnings(columns 2, 3, and 4)		
Lag length	4	**28**
Polynomial degree	1	**2**
Total effect (%)	0.27	0.52
Mean lag (quarters)	0.72	2.63
Mean lag (years)	0.18	0.66
Duration (quarters)	1.43	5.27
Duration (years)	0.36	1.32
Adjusted R^2 (%)	35.78	34.91
Sample size	154	154

This table reports results from regression of current GDP growth on past aggregate accounting R&D and other control variables.

$G\_GDP_q = \beta_0 + \sum_{t=0}^{k}\beta_{1,\ q\text{-}t}\ G\_XRD_{q\text{-}t} + \sum_{t=0}^{m}\beta_{2,\ q\text{-}t}\ G\_PreRD\_Earn_{q\text{-}t} + \beta_3\ G\_GDP_{q\text{-}1} + \beta_4 Yield_{q\text{-}1} + \beta_5\ Spread_{q\text{-}1} + \beta_6\ Return\_12_{q\text{-}1} + \varepsilon_q$ (1)

$G\_XRD_{q\text{-}t}$ and $G\_PreRD\_Earn_{q\text{-}t}$ are aggregate accounting R&D and pre-R&D earnings for quarter q-t, respectively. *G_XRD* is the weighted average of the year-over year change in quarterly R&D scaled by one-quarter lagged quarterly sales, with the weight being the market capitalization of the firm at the beginning of the quarter. *G_PreRD_Earn* is computed similarly except for the year-over-year change in quarterly earnings before R&D expenditures. All accounting variables used to derive *G_XRD* and *G_PreRD_Earn* are adjusted for inflation. G_GDP_q is quarter-over-quarter seasonally adjusted annualized real GDP growth for quarter q. $Yield_{q\text{-}1}$ is the yield on the one-year constant maturity Treasury bill measured one month after quarter q-1 ends. $Spread_{q\text{-}1}$ is the yield on the ten-year constant maturity Treasury bond minus the yield on the one-year constant maturity T-bill measured one month after quarter q-1 end. $Return\_12_{q\text{-}1}$ is the quarterly buy-and-hold stock market returns measured over 12 months ending in the first month after quarter q-1 ends. For the return, we use the value weighted CRSP index (including distributions) to measure the stock market portfolio. We obtain accounting data from the Compustat quarterly database. We obtain GDP data from the Bureau of Economic Analysis (BEA), data on yields from the Federal Reserve Board's H15 Report, and data on stock market returns from the CRSP Monthly Index File. We mitigate the effect of outliers by deleting firm-quarter observations that fall in the top and bottom one percentile of each quarterly cross-section of aggregate level and growth of R&D expense and pre-R&D earnings. We use the Almon (1965) distributed lag model for all regressions. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively, using two-tail t-tests. T-statistics are reported in parentheses next to the corresponding coefficient estimates. Our sample includes 154 quarters over the period Q1:1978 – Q3:2016.

The reported estimates and t-statistics of $G\_XRD_{q\text{-}t}$ and $G\_PreRD\_Earn_{q\text{-}t}$ are the average of the significant estimates and t-statistics of the series of $G\_XRD_{q\text{-}t}$ and $G\_PreRD\_Earn_{q\text{-}t}$, respectively. The "sig. lags" column indicates the lags of $G\_XRD_{q\text{-}t}$ and $G\_PreRD\_Earn_{q\text{-}t}$ that are significant at the 10 percent level or below. The following equations describe the vital statistics in this table.

- Total effect of past aggregate R&D investments on current GDP growth = $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$
- Mean lag (quarters) = $\sum_{t=0}^{k} t\beta_{1,\ q\text{-}t} / \sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$
- Mean lag (years) = Mean lag (quarters) / 4
- Duration (quarters) = Mean lag (quarters) $\times$ 2
- Duration (years) = Duration (quarters) / 4

Table 3
Channel analyses.

	[1]			[2]			[3]			[4]		
Dependent variable	$G\_Personal\_Cons_q$			$G\_Bus\_Invest_q$			G_Export_q			$G\_Gov\_Spend_q$		
	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags
$G\_XRD_q \rightarrow_{q-k}$	**0.647**	***(3.12)******	**5 – 23**	**2.319**	***(1.81)****	**13 – 20**	**−0.209**	**(-2.42)****	**4 – 14**	**0.00**	***(0.00)***	
$G\_PreRD\_Earn_q \rightarrow_{q-m}$	0.000	*(0.66)*		0.521	*(1.80)**	0	0.031	*(3.79)****	0 – 7	0.00	*(0.00)*	
G_GDP_{q-1}	0.071	*(0.84)*		0.542	*(1.15)*		−0.049	*(-1.59)*		0.103	*(0.96)*	
$Yield_{q-1}$	−0.213	*(-1.76)**		−1.304	*(-2.12)***		0.308	*(9.35)****		0.232	*(2.00)***	
$Spread_{q-1}$	−0.275	*(-1.21)*		1.546	*(1.23)*		0.305	*(3.45)****		−0.286	*(-0.83)*	
$Return\_12_{q-1}$	0.027	*(2.30)***		0.190	*(2.91)****		−0.008	*(-1.96)**		−0.023	*(-1.35)*	
For R&D												
Lag length		28			26			18			15	
Polynomial degree		2			2			2			2	
Total effect (%)		12.81			18.55			−2.30			N/A	
Mean lag (quarters)		14.04			16.53			8.94			N/A	
Mean lag (years)		3.51			4.13			2.24			N/A	
Duration (quarters)		28.09			33.07			17.89			N/A	
Duration (years)		7.02			8.27			4.47			N/A	
Adjusted R^2 (%)		28.51			28.13			53.89			19.55	
Sample size		154			154			154			154	

This table reports results for the following equation:
$Y_q = \beta_0 + \sum_{t=0}^{k}\beta_{1,\ q\text{-}t}\ G\_XRD_{q-t} + \sum_{t=0}^{m}\beta_{2,\ q\text{-}t}\ G\_PreRD\_Earn_{q-t} + \beta_3\ G\_GDP_{q-1} + \beta_4 Yield_{q-1} + \beta_5\ Spread_{q-1} + \beta_6\ Return\_12_{q-1} + \varepsilon_q$ (2).
Y stands for four components of real GDP growth. *G_Personal_Cons* measures growth in personal consumption expenditures. *G_Bus_Invest* measures growth in businesses' purchases to create new consumer goods. *G_Export* measures growth in net exports, i.e., exports minus imports. *G_Gov_Spend* measures growth in governmental expenditures. All components of GDP growth are annualized quarter-over-quarter changes in real terms, i.e., adjusted for inflation. G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$ are aggregate accounting R&D and pre-R&D earnings for quarter q-t, respectively. *G_XRD* is the weighted average of the year-over year change in quarterly R&D scaled by one-quarter lagged quarterly sales, with the weight being the market capitalization of the firm at the beginning of the quarter. *G_PreRD_Earn* is computed similarly except for the year-over-year change in quarterly earnings before R&D expenditures. All accounting variables used to derive *G_XRD* and *G_PreRD_Earn* are adjusted for inflation. $Yield_{q-1}$ is the yield on the one-year constant maturity Treasury bill measured one month after quarter q-1 ends. $Spread_{q-1}$ is the yield on the ten-year constant maturity Treasury bond minus the yield on the one-year constant maturity T-bill measured one month after quarter q-1 end. $Return\_12_{q-1}$ is the quarterly buy-and-hold stock market returns measured over 12 months ending in the first month after quarter q-1 ends. For the return, we use the value weighted CRSP index (including distributions) to measure the stock market portfolio. We obtain accounting data from the Compustat quarterly database. We obtain GDP data from the Bureau of Economic Analysis (BEA), data on yields from the Federal Reserve Board's H15 Report, and data on stock market returns from the CRSP Monthly Index File. We mitigate the effect of outliers by deleting firm-quarter observations that fall in the top and bottom one percentile of each quarterly cross-section of aggregate level and growth of R&D expense and pre-R&D earnings. We use the Almon (1965) distributed lag model for all regressions. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively, using two-tail t-tests. T-statistics are reported in parentheses next to the corresponding coefficient estimates. Our sample includes 154 quarters over the period Q1:1978 – Q3:2016.
The reported estimates and t-statistics of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$ are the average of the significant estimates and t-statistics of the series of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$, respectively. The "sig. lags" column indicates the lags of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$ that are significant at the 10 percent level or below. The following equations describe the vital statistics in this table.

- Total effect of past aggregate R&D investments on current GDP growth = $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$
- Mean lag (quarters) = $\sum_{t=0}^{k} t\beta_{1,\ q\text{-}t}$ / $\sum_{t=0}^{k}\beta_{1,\ q\text{-}t}$.
- Mean lag (years) = Mean lag (quarters) / 4.
- Duration (quarters) = Mean lag (quarters) × 2.
- Duration (years) = Duration (quarters) / 4.

only four lags of pre-R&D earnings. This pattern persists when we control for other determinants of GDP growth (columns [5] and [6]).

2.2. Channel analyses

GDP consists of four components – personal consumption, business investment, net exports, and governmental spending. Personal consumption refers to consumer spending on goods and services.[18] Business investment refers to *new* investments in non-residential fixed assets and inventories that companies make to satisfy consumer demand.[19] Net exports refer to the difference between exports and imports of goods.[20] Governmental spending refers to spending by the U.S. governmental units at the federal, state, and local levels.[21]

[18] Personal consumption accounted for 69.45 percent of the U.S. real GDP in 2018 (BEA, 2019, Table 1.1.6).
[19] In 2018, business investment accounted for 18.03 percent of the U.S. real GDP.
[20] Since the mid-1970s, the U.S. has been having more imports than exports, creating a trade deficit. In 2018, net exports accounted for a negative 4.94 percent of the U.S. real GDP.
[21] In 2018, governmental spending accounted for 17.30 percent of the U.S. real GDP.

Table 4
Aggregate accounting real R&D growth, real GDI growth, and its components.

	[1]			[2]			[3]			[4]			[5]		
Dependent variable	G_GDI_q			G_NOS_q			G_Comp_q			G_COFC_q			G_Tax_q		
	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags	Coef.	t-stat	Sig. lags
$G\_XRD_q \rightarrow_{q-k}$	**0.581**	***(2.95)******	**0–2 7–23**	**0.535**	***(2.40)*****	**0–3 10–19**	**0.813**	***(2.31)*****	**4 – 21**	**0.292**	***(1.89)****	**15–23**	**1.288**	***(2.66)******	**11–42**
$G\_PreRD\_Earn_q \rightarrow_{q-m}$	0.101	*(1.84)**	0	0.000	*(0.36)*		0.133	*(2.31)***	0 – 1	0.000	*(0.95)*		0.000	*(0.87)*	
G_GDP_{q-1}	0.168	*(1.88)**		−0.051	*(-0.56)*		−0.114	*(-1.29)*		0.553	*(7.13)****		0.036	*(0.34)*	
$Yield_{q-1}$	−0.252	*(-1.69)**		−0.312	*(-0.71)*		−0.292	*(-1.54)*		−0.066	*(-0.85)*		−1.310	*(-2.18)***	
$Spread_{q-1}$	−0.037	*(-0.13)*		1.964	*(2.17)***		−0.939	*(-2.52)***		−0.224	*(-1.40)*		−1.025	*(-1.28)*	
$Return\_12_{q-1}$	0.043	*(2.97)****		0.015	*(0.32)*		0.082	*(4.24)****		0.007	*(0.95)*		0.052	*(1.69)**	
For R&D															
Lag length		28			26			27			27			50	
Polynomial degree		2			2			2			2			2	
Total effect (%)		11.62			7.49			14.64			2.63			22.10	
Mean lag (quarters)		18.77			37.71			12.50			19.08			51.04	
Mean lag (years)		4.69			9.43			3.12			4.77			12.76	
Duration (quarters)		37.54			75.43			24.99			38.16			102.09	
Duration (years)		9.39			18.36			6.25			9.54			25.52	
For pre-R&D earnings															
Lag length		3			3			3			3			3	
Polynomial degree		1			1			1			1			1	
Total effect (%)		0.10			N/A			0.27			N/A			N/A	
Mean lag (quarters)		N/A			N/A			0.36			N/A			N/A	
Mean lag (years)		N/A			N/A			0.09			N/A			N/A	
Duration (quarters)		N/A			N/A			0.72			N/A			N/A	
Duration (years)		N/A			N/A			0.18			N/A			N/A	
Adjusted R^2 (%)		35.51			20.64			33.38			54.34			14.92	
Sample size		154			154			154			154			154	

This table reports results from Almon regression of current GDI growth and its components on past aggregate accounting R&D.

$Y_q = \beta_0 + \sum_{t=0}^{k}\beta_{1,\ q-t}\ G\_XRD_{q-t} + \sum_{t=0}^{m}\beta_{2,\ q-t}\ G\_PreRD\_Earn_{q-t} + \beta_3\ G\_GDP_{q-1} + \beta_4 Yield_{q-1} + \beta_5\ Spread_{q-1} + \beta_6\ Return\_12_{q-1} + \varepsilon_q$ (3)

Y stands for *G_GDI*, *G_NOS*, *G_Comp*, *G_COFC*, and *G_Tax*, which are the quarter-over-quarter growth in seasonally adjusted annualized real Gross Domestic Income (GDI), Net Operating Surplus (NOS), Employee Compensation (Comp), and Taxes on Production and Imports less Subsidies (Tax), respectively. *G_XRD* is the weighted average of the year-over year change in quarterly R&D scaled by one-quarter lagged quarterly sales, with the weight being the market capitalization of the firm at the beginning of the quarter. *G_PreRD_Earn* is computed similarly except for the year-over-year change in quarterly earnings before R&D expenditures. All accounting variables used to derive *G_XRD* and *G_PreRD_Earn* are adjusted for inflation. $Yield_{q-1}$ is the yield on the one-year constant maturity Treasury bill measured one month after quarter q-1 ends. $Spread_{q-1}$ is the yield on the ten-year constant maturity Treasury bond minus the yield on the one-year constant maturity T-bill measured one month after quarter q-1 end. $Return\_12_{q-1}$ is the quarterly buy-and-hold stock market returns measured over 12 months ending in the first month after quarter q-1 ends. For the return, we use the value weighted CRSP index (including distributions) to measure the stock market portfolio. We obtain accounting data from the Compustat quarterly database. We obtain GDP data from the Bureau of Economic Analysis (BEA), data on yields from the Federal Reserve Board's H15 Report, and data on stock market returns from the CRSP Monthly Index File. We mitigate the effect of outliers by deleting firm-quarter observations that fall in the top and bottom one percentile of each quarterly cross-section of aggregate level and growth of R&D expense and pre-R&D earnings. We use the Almon (1965) distributed lag model for all regressions. ***, **, and * indicate statistical significance at 1 percent, 5 percent, and 10 percent level, respectively, using two-tail t-tests. T-statistics are reported in parentheses next to the corresponding coefficient estimates. Our sample includes 154 quarters over the period Q1:1978 – Q3:2016.

The reported estimates and t-statistics of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$ are the average of the significant estimates and t-statistics of the series of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$, respectively. The "sig. lags" column indicates the lags of G_XRD_{q-t} and $G\_PreRD\_Earn_{q-t}$ that are significant at the 10 percent level or below. The following equations describe the vital statistics in this table.

- Total effect of past aggregate R&D investments on current GDP growth = $\sum_{t=0}^{k}\beta_{1,\ q-t}$
- Mean lag (quarters) = $\sum_{t=0}^{k} t\beta_{1,\ q-t} / \sum_{t=0}^{k}\beta_{1,\ q-t}$
- Mean lag (years) = Mean lag (quarters) / 4
- Duration (quarters) = Mean lag (quarters) × 2
- Duration (years) = Duration (quarters) / 4

Because publicly traded firms invest in R&D projects to generate innovations that create value for customers, we expect an increase in aggregate R&D expenditures from all publicly traded firms to increase future consumers' personal consumption. Increased personal consumption leads to increased demand for products, which prompts firms to invest in new inventories and fixed assets to enhance their production capacity.[22] As publicly traded firms increase their R&D spending to create product and process innovations, they frequently outsource the manufacturing driven by such innovations to foreign countries to benefit from the relatively cheaper production (labor and material) costs and potentially less stringent regulations. Once the products are manufactured, U.S. firms import them back to the U.S., creating a trade deficit (decreased net export).[23] We offer no prediction for the effect of corporate R&D expenditures on governmental spending because the government spends for both economic and political reasons.[24]

Consistent with our predictions, Table 3 shows that aggregate R&D growth strongly predicts real growth in all components of GDP except for government spending. Thus, increases in corporate R&D expenditures create product and process innovations that directly increase consumer spending (column [1]), generate growth in business investment (column [2]), and increase imports relative to exports (column [3]).

3. Additional analyses and robustness checks

Our baseline results are robust to the exclusion of defense spending from GDP and defense-related industries from the sample; to tests of reverse causality; and to out-of-sample tests. In additional analyses, we find that aggregate accounting R&D and pre-R&D earnings can predict real GDP growth even after controlling for macroeconomists' GDP growth forecasts. Thus, macro forecasters do not fully incorporate information about accounting R&D into their forecasts even though this information is publicly available and doing so would significantly increase their forecast accuracy. This is consistent with the general finding in prior micro-to-macro studies that macroeconomists do not fully incorporate accounting information in their forecasts of macroeconomic variables.[25]

We further test whether aggregate accounting R&D can predict future GDI and its components. According to Laurion and Patatoukas (2016) and Abdalla, Carabias, and Patatoukas (2021), one can measure economic output using either GDP or GDI, which capture the product side and income side of output, respectively. GDI is the sum of net operating surplus, employee compensation, consumption of fixed capital, and taxes on production and imports less subsidies.[26] According to Abdalla et al. (2021), while GDP and GDI are conceptually similar, they are different on a practical level due to different estimation methods and largely different data sources. To triangulate the baseline results, we test whether aggregate accounting R&D can also predict GDI and its components. We rerun equation (1) while substituting GDI and its components for GDP growth. The results (Table 4) show that aggregate accounting R&D growth has significant predictive ability with respect to growth in GDI and its components over varying lags. This analysis strengthens our baseline results on the usefulness of aggregate R&D expenditures in predicting macroeconomic outcome variables important in economic policy making.

4. Conclusions

Our study extends prior research on the usefulness of accounting information at the aggregate level and has practical implications for macro forecasting and public policy making with respect to innovative activities of publicly listed firms. (KP, 2014a; KP, 2014b) demonstrate that aggregate accounting earnings growth can predict future *nominal* and *real* GDP growth. We extend this literature by decomposing accounting earnings into the R&D and pre-R&D components. Using the Almon (1965) finite distributed lag model, we find that both components can predict future *real* GDP growth with different lag structures. Importantly, decomposing earnings and assigning theoretically appropriate lag structures to each component significantly increase the explanatory power of aggregate accounting data with respect to future real GDP growth. Aggregate R&D expenditures can predict real GDP growth through the personal consumptions, business investment, and net export channels of GDP. Moreover, they can also predict real GDI growth and its components. The results are robust to various robustness checks and endogeneity tests.

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[22] For example, consumers increase market demand for Apple's iPhone products as they learn about the benefits of the iPhone.

[23] For example, while Apple created the technology for iPhone, the company has the phones manufactured in China and other developing countries before importing them back to the U.S.

[24] While R&D spending by military contractors can lead to future military spending by the federal government, other types of governmental spending such as health care and social security are unlikely to rely on corporate R&D spending.

[25] For brevity, these results are untabulated but are available upon request.

[26] Net operating surplus is the business income before financing costs and business transfer payments, consisting of the net operating surplus of private enterprises and the current surplus of government enterprises. Employee compensation is the wage and salary disbursements and supplements to wages and salaries received by U.S. residents, including wages and salaries received from the rest of the world. Consumption of fixed capital is the decline in the value of the stock of fixed assets due to wear and tear, obsolescence, accidental damage, and aging. Abdalla et al. (2021) discuss these components in detail.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Summary of variables used in the analyses

Variable	Description*	Sources
G_GDPq	Growth in GDP from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
$G\_Personal\_Cons_q$	Growth in personal consumption expenditures (Personal_Cons) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
$G\_Bus\_Invest_q$	Growth in business investments (Bus_Invest) to create new goods and services from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_Export_q	Growth in net exports (Export) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
$G\_Gov\_Spend_q$	Growth in governmental spending (Gov_Spend) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_GDI_q	Growth in Gross Domestic Income (GDI) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_NOS_q	Growth in net operating surplus (NOS) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_Comp_q	Growth in employee compensation (COMP) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_COFC_q	Growth in consumption of fixed capital (COFC) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_Tax_q	Growth in taxes on production and import less subsidies (TAX) from quarter q-1 to quarter q	Bureau of Economic Analysis (BEA)
G_XRD_q	Nominal aggregate accounting R&D expense growth from quarter q-4 to quarter q $G\_XRD_q = \sum_{i=1}^{N} w_{iq} \times [(XRD_{iq}/Sales_{iq}) - (XRD_{i(q-4)}/Sales_{i(q-4)})]$ *Where*: XRD_i = firm i's quarterly after-tax R&D expense, where tax rate is 35 percent $Sales_i$ = firm i's quarterly sales revenue $w_{iq} = Market\_Cap_{i(q-1)} / \sum_{i=1}^{N} Market\_Cap_{i(q-1)}$ N = number of listed firms in quarter q $Market\_Cap_{i(q-1)} = Shares\ outstanding_{i(q-1)} \times Price\ per\ share_{i(q-1)}$	Compustat quarterly database
$G\_PreRD\_Earn_q$	Nominal aggregate accounting pre-R&D earnings growth from quarter q-4 to quarter q $G\_PreRD\_Earn_q = \sum_{i=1}^{N} w_{iq} \times [(Pre\_RD\_Earn_{iq}/Sales_{iq}) - (Pre\_R\&D\_Earn_{i(q-4)}/Sales_{i(q-4)})]$ *Where*: $Pre\_RD\_Earn_{iq}$ = firm i's net income before after-tax R&D expense in quarter q $= Earn_{iq} + XRD_{iq}(1 - 0.35)$ $Sales_{iq}$ = firm i's sales revenue in quarter q $w_{iq} = Market\_Cap_{i(q-1)} / \sum_{i=1}^{N} Market\_Cap_{i(q-1)}$; N = number of listed firms in quarter q $Market\_Cap_{i(q-1)} = Shares\ outstanding_{i(q-1)} \times Price\ per\ share_{i(q-1)}$	Compustat quarterly database

(*continued on next page*)

Appendix A (*continued*)

Variable	Description*	Sources
$Return\_12_{q-1}$	Buy-and-hold quarterly return for 12 months ending in the first month after quarter q-1 ends $Return\_12_{q-1} = \exp\left[\sum_{t=1}^{12}\log(1 + vwretd_t)\right] - 1$ *Where*: $Vwretd_t$ = value-weighted return including dividend for month t	CRSP Monthly Index File
$Yield_{q-1}$	Yield on the one-year constant maturity Treasury bill measured one month after quarter q-1 ends	Federal Reserve Board's H15 Report
$Spread_{q-1}$	Yield on the ten-year constant maturity Treasury bond minus the yield on the one-year constant maturity T-bill measured one month after quarter q-1 end $Spread_{q-1} = Yield\_10_{q-1} - Yield_{q-1}$ *Where*: $Yield\_10_{q-1}$ = yield on ten-year constant maturity Treasury bond	Federal Reserve Board's H15 Report

*The growth for all macroeconomic variables (GDP, GDI, and their components) is computed as follows: $G\_X_q = (G\_X_q/G\_X_{q-1})^4 - 1$.

*Where X is the macroeconomic variable under consideration and q is quarter.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jaccpubpol.2021.106901.

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